NORMAL ECG RECOGNITION FOR EXPRESS-DIAGNOSTICS BASED ON SCALE-SPACE REPRESENTATION AND DYNAMIC MATCHING

Nataliya Bilous, Michael Bondarenko, Gleb Kobzar,
Alexey Krasov, Artyom Rogozyanov

Abstract: A novel approach of normal ECG recognition based on scale-space signal representation is proposed. The approach utilizes curvature scale-space signal representation used to match visual objects shapes previously and dynamic programming algorithm for matching CSS representations of ECG signals. Extraction and matching processes are fast and experimental results show that the approach is quite robust for preliminary normal ECG recognition.

Keywords: electrocardiogram, express-diagnostics, curvature scale-space, dynamic programming, dynamic time wrapping.

ACM Classification Keywords: I.5 Pattern Recognition.

Conference: The paper is selected from International Conference "Intelligent Information and Engineering Systems" INFOS 2008, Varna, Bulgaria, June-July 2008

Introduction

Automatic diagnostics of cardiac diseases is the traditional task of medical cybernetics. At current large experience is accumulated in this area. In particular attempts of complete automation of heart activity diagnostics have failed to be enough robust comparatively to traditional human diagnostics. The most essential stage of traditional ECG analysis is recognition of its major elements, which consist of finding out the QRS-complex, selection of it's characteristic points (tops of Q, R, S indents, scopes of indents and their borders).

The results of element analysis (annotation) and measuring of their parameters are used for ECG interpretation with purpose of correct diagnosis. Two basic categories of algorithms, applied in different systems of automatic diagnostics currently exist. Algorithms that design logic of doctor-diagnostician fall into the first category. The algorithms of the second category as a rule are based on the methods of multidimensional statistical analysis and theory of possibility.

Indisputable advantage of medical algorithms - in possibility of their rapid realization. It is conditioned by the fact that they concentrate experience of diagnostics accumulated in medicine and do not require preliminary teaching. Diagnostic possibilities of such algorithms are limited to the modern level of medicine development and quality of concrete algorithms – to the competence of persons assembling them as technicians and medics.

Advantage of unmedical diagnostic algorithms is that they can utilize any parameters of electrocardiogram representation. Due to it backlogs of information which in clinical practice remain unutilized appear accessible for such algorithms. The lack of these algorithms is complication of teaching. In case substantial difficulties are related to the selection of the well probed patients with diseases which an automat must learn to distinguish. Nevertheless, the algorithms of the second category are considered more perspective, because access to the new information should make diagnostics more effective.

Various automatic algorithms of the second group have been proposed, such as the threshold-crossing intervals X and the auto-correlation function [1] and algorithms based on neural-networks [2]. Time-frequency (t — f) analysis [3] and wavelet analysis [4] have also been used. All these algorithms suppose finding one special disease or detecting that ECG signal could be classified as normal.

This article focuses on building express-diagnostics system for ECG analysis that is to be performed at home or in non-medical environments by professional doctors or even users having no medical knowledge. The diagnostic result s of such system corresponds to three possible binary decisions: normal ECG, disease, not known.

We propose a novel approach of normal ECG recognition which is based on scale-scale signal representation used for geometric object shape recognition previously - curvature scale-space (CSS) and our dynamic programming algorithm for matching ECG signal represented as CSS descriptors. Though the idea of scale-scale signal representation for ECG analysis is far not new [5] including the fact that wavelets are multi-scale by nature the approach proposed may have some valuable advantages over existing scale-scale approaches.

The article is organized in 4 main sections. The first section describes CSS briefly as it's not a well-known technology in medical signal processing. The second section introduces how to apply CSS to ECG signals. The third section focuses on dynamic programming matching algorithm proposed. And the last chapter describes some tests performed.

Curvature Scale Space representation of shape

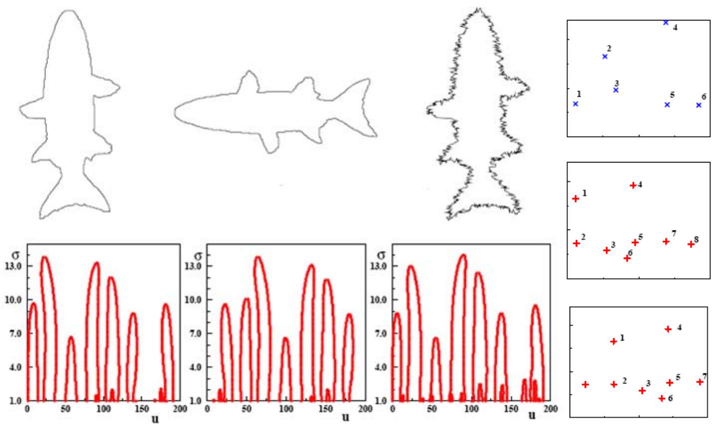
The Theory of Scale-Scale Signal Representation was introduced by Vitkin and Coendric in 1983. The methodology consist in embedding a measured signal into a one-parametric family of derived signals, the scale-space, where the parameter, denotes scale parameter $\sigma \in \Re_+$, is intended to the current level of scale. For a signal $f:\Re \to \Re$, the scale-space representation $L:\Re \times \Re_+ \to \Re$ is defined as [6]:

$$L(x;0) = f(x). \tag{1}$$

And representation at coarser scales are given by convolution of the given signal with Gaussian kernels of successively increasing width:

$$L(x,\sigma) = g(x,\sigma) * f(x). \tag{2}$$

Curvature Scale-Space was introduced later by Mokharitan for geometric object shape representation as follows [7]. Having curvature of each closed contour $L(x,\sigma)$ points calculated, curvature zero-crossing points can be found easily. Then Curvature Scale-Space is built by locating zero-crossings in (u,σ) space (u - normalized arc length, σ - Gaussian filter [7]. The resulting CSS can be represented as a binary image of CSS (fig.1). Cross-sections of CSS by horizontal lines define position of zero-crossing points on the corresponding $L(x,\sigma)$ contour curve.



a b c d

Fig. 1. Contour curves and corresponding CSS Images: a – contour, б – it's rotation, в – noise effect

It is obvious that CSS images of normalized curves are invariant to affine transformations and noise. Rotation of an object causes circular shift of it's CSS representation (fig.1a,b). The same effect is caused by the change of contour starting point. Because of normalization scaling also don't affect the view of CSS. Picture 1 (c) also shows that noise effects in appearance of small arcs at the low levels of σ but don't affect main arcs.

These properties of CSS image are used for effective representation and recognition of object shapes. It should be also noted that successful identification of shapes based on CSS representation don't require CSS Images themselves but arc maximums only [7]. The set of CSS maximas consists of pairs and form well-known CSS description which was selected as one of the main shape descriptors for MPEG-7 standard.

Application of CSS to ECG Representation

Curvature Scale-Space representation and matching process was introduced for closed curve contours only and are not suitable for signal analysis. We will show that it is possible to adapt CSS for ECG representation in this section and ECG matching based on such representation in the next section.

As curvature scale-space methodology has it's root's in multi-scale signal representation area switching back from closed contours to signal segments representation is very easy. Signal curvature zero-crossing points may be acquired in the same way calculating the first and the second discrete differences (fig. 2).

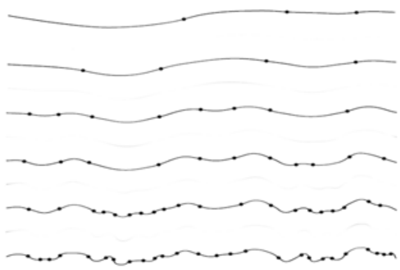


Fig. 2. Evolution of the signal and appropriate curvature zero-crossing points.

CSS images of such zero-crossings found on each scale of ECG signal evolving will look the same as for geometric object shape contour (fig.1). The only difference here is in representation of CSS image maxima which affects matching process also. As closed contour may be started to detect from different points CSS image is also circular. In a difference an ECG signal starts and finishes at certain points. So CSS image for ECG and the set of maxima as well is not be shifted during acquisition and matching process.

Matching CSS Representations of ECG

Let's first analyze CSS matching algorithm for closed contour curves introduced by Mokhtarian [7]. As mentioned before, every object in the database is represented by the locations of the maxima of it's CSS images. Matching algorithm compares two sets of maxima and assigns a matching value to them which represents the similarity between the actual boundaries of objects. The first step in CSS matching is to shift one of the two sets of maxima so that the effect of randomly selected starting points is compensated. Since the exact value of required shift is not available, we choose several values for it and then find the best match among them. The vest choice is a value that shifts one CSS image so that its major maximum covers the major maximum of the other CSS image. Other possible choices are those values which accomplish the same with the second and possibly the third major maxima. The matching value will be the summation of the straight line distances between the matched pairs plus the vertical coordinates of the unmatched maxima.

Obviously as the nature of curves differs for contours and signals matching algorithm of CSS representations introduced by Mokhtarian with it's main principle to shift maximums is not suitable for CSS representations of ECG signals. Moreover the algorithm described will fail to match curves with large dissimilarities of structure distances (heart rhythm change).

A different algorithm of matching CSS representations of ECG based on dynamic programming is proposed. It is organized in the same way as Dynamic Time Warping (DTW).

Having two sets of maxima $Q= q_1,q_2,\ldots,q_i,\ldots,q_n$ ($q_i = (\sigma_i, x_i)$, where σ is a scale parameter and x is position of the maxima) and $C=c_1,c_2,\ldots,c_j,\ldots,c_m$ ($c_i = (\sigma_i, x_i)$) of length n and m respectively matching of these sets using proposed DP matching algorithm requires to construct an n-by-m matrix (DP matrix) where the (i^{th}, j^{th}) element of the matrix contains the distance $d(q_i,c_j)$ between the two points q_i and c_j (in a metric defined below). Each matrix element (i,j) corresponds to the alignment between the points q_i and c_j. This is illustrated in Figure 3a. A warping path W, is a continuous (in the sense stated below) set of matrix elements that defines a mapping between Q and C. The k^{th} element of W is defined as $w_k = (i,j)_k$ so we have:

$$W = w_1, w_2, \ldots, w_k, \ldots, w_K \quad \ldots\ldots \max(m,n) , K < \tag{3}$$

The warping path is typically subject to several constraints:

- Boundary conditions: $w_1 = (1,1)$ and $w_K = (m,n)$, simply stated, this requires the warping path to start and finish in diagonally opposite corner cells of the matrix.

- Continuity: Given $w_k = (a,b)$ then $w_{k-1} = (a',b')$ where $a–a'<=1$ and $b-b'<=1$. This restricts the allowable steps in the warping path to adjacent cells (including diagonally adjacent cells).

- Monotonicity: Given $w_k = (a,b)$ then $w_{k-1} = (a',b')$ where $a–a'>= 0$ and $b-b'>= 0$. This forces the points in W to be monotonically spaced in time.

There are exponentially many warping paths that satisfy the above conditions, however we are interested only in the path which minimizes the warping cost:

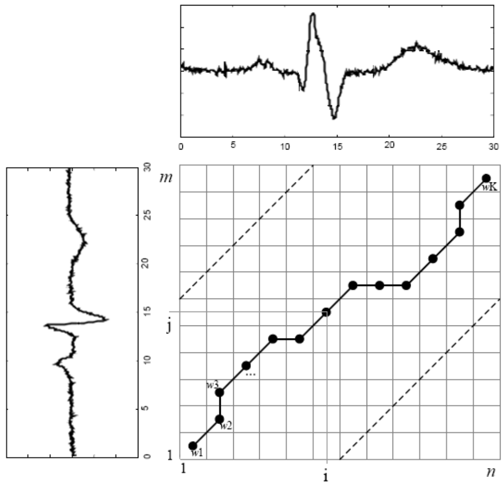


Fig. 3. Dynamic matching of two ECG signals

$$Cost(Q,C) = \min\left\{ \sqrt{\sum_{k=1}^{K} w_k} \; / K \right. \tag{4}$$

This path can be found very efficiently using dynamic programming to evaluate the following recurrence which defines the cumulative distance $\gamma(i,j)$ as the distance $d(i,j)$ found in the current cell and the minimum of the cumulative distances of the adjacent elements:

$$\gamma(i,j) = d(q_i,c_j) + \min\{ \gamma(i-1,j-1) , \gamma(i-1,j) , \gamma(i,j-1) \}$$

The difference from DTW here is the way to calculate values $d(q_i,c_j)$ which is the basement of any DP algorithm. We propose to calculate $d(q_i,c_j)$ according to matching of two points or skipping the match which corresponds to diagonal, horizontal and vertical movements from w_{k-1} to w_k in DP matrix. Following formulas are used in different cases:

$$\begin{aligned} &d_{match}(q_i,c_j) = \|q_i - c_j\|, \\ &d_{skipi}(q_i,c_j) = \sigma_i, \\ &d_{skipj}(q_i,c_j) = \sigma_j, \end{aligned} \tag{5}$$

where $d_{match}(q_i,c_j)$ - distance for matching two points or a diagonal movement,

$d_{skipi}(q_i,c_j)$ - distance for skipping the point q_i or a horizontal movement,

$d_{skipj}(q_i,c_j)$ - distance for skipping the point q_j or a vertical movement,

$\|q_i - c_j\| = \sqrt{(\sigma_i - \sigma_j)^2 + (x_i - x_j)^2}$.

Such formulation of $d(q_i,c_j)$ has already been proven in practical application of geometric shape matching as a part of Mokhtarian's algorithm.

Finally the cost of matching could be found in $\gamma(n,m)$ using backtracking algorithm while building the optimal path W.

Experimental Results

51 ECG signals was selected for testing from the international ECG database PhysyoNet (Physikalisch-Technische Bundesanstalt – PTB, the National Metrology Institute of Germany). This database was assembled by doctor Michael Oeff, M.D. (the Department of Cardiology of University Clinic Benjamin Franklin in Berlin, Germany) from ECG's of healthy volunteers and patients having different classes of heart diseases.

Table 1. Distribution of classes

Diagnostic class	Number of ECG signals
Myocardial infarction	5
Cardiomyopathy/Heart failure	8
Bundle branch block	5
Dysrhythmia	4
Myocardial hypertrophy	5
Valvular heart disease	5
Myocarditis	5
Miscellaneous	4
Healthy controls	10
Total	51

Techniques of CSS representation and dynamic matching were realized as a computer program which was tested on the assembled database of ECG signals.

As a result of testing the developed program on three takings (average cost for I, II and III taking) the table of likeness for all of ECG signals of the base was acquired against "normal" ECG signal depicted earlier. Setting the threshold of dissimilarity to $TP=119$ no unhealthy man ECG of was treated as "normal". And 1 of 10 healthy ECG signals was treated as "not normal". Following the well known technique of automatic ECG interpretation quality estimation [9] we assume that all database signals are verified (normal forms and pathological forms). Then counting up the general number of the followings events: correct classification of normal ECG (TN), improper classification of normal ECG as pathological (FP), improper classification of pathological ECG as normal (FN), correct classification of pathological ECG (TP).

In total, quality of ECG interpretation is calculated as "probability that classification is correct" according to the following formula:

$$TA = \frac{TP + TN}{TP + FP + TN + FN} 100\% \tag{6}$$

Thus according to experiment results $TP=41$, $TN=9$, $FP=0$, $FN=1$ and resulting $TA=98\%$. After introduction of the third diagnostic result – "not known" $FN=0$ may be achieved. In the case if a user received "not known" result he can repeat the measurements. And if the same result achieved again it would be recommended to consult with professional doctor-cardiologist.

Conclusion

A novel approach of normal ECG recognition based on scale-space signal representation is proposed. The approach uses curvature scale-space signal representation used to match visual objects shapes previously and dynamic programming algorithm for matching CSS representations of ECG signals. The main advantage of the approach over the existing scale-space representations (ex. wavelet based) and correlation methods (including direct dynamic and derivative dynamic time warping considered in the article) is faster extraction and matching process as it is done in feature space.

Experimental results show that the approach is quite robust for preliminary normal ECG recognition. It is planned to conduct larger tests on different ECG databases and comparative tests to compare the quality of diagnostics and the rapidness with other interpretation techniques.

Bibliography

[1] R.H. Clayton, A. Murray, R.W.F. Campbell, Comparison of four techniques for recognition of ventricular fibrillation of the surface ECG, Med. Biol. Eng. Comp. 31 (1993), pp. 111—117.

[2] K. Minami, H. Nakajima, T. Toyoshima, Real-time discrimination of ventricular tachyarrhythmia with Fourier transform neural network, IEEE Trans. Biomed. Eng. 46 (2) (1999), pp. 179—185.

[3] V.X. Afonso, W.J. Tompkins, Detecting ventricular fibrillation, IEEE Eng. Med. Biol. 14 (1995) pp. 152—159.

[4] A.S. Al-Fahoum, I. Howitt, Combined wavelet transformation and radial basis neural networks for classifying life threatening cardiac arrhythmias, Med. Biol. Eng. Comput. 37 (1999), pp. 566—573.

[5] F. Jager; I. Koren; L. Gyergyek Multiresolution representation and analysis of ECG waveforms, Computers in Cardiology Proceedings. Volume 23-26 (1990), PP.:547 – 550

[6] T. Linderberg Scale Space Theory in Computer Vision, Kluwer Academic Publishers. (1994), 440p.

[7] F. Mokhtarian, S. Abbasi, J. Kittler Efficient and Robust Retrieval by Shape Content through Curvature Scale Space, Int. Workshop on Image DataBases and Multimedia Search (1996), pp. 35-42.

[8] H. Strik, L. Boves Averaging physiological signals with the use of a DTW algorithm. In Proceedings of SPEECH'88, 7th FASE Symposium, Edinburgh, Book 3 (1988), pp. 883-890.

[9] Medical electrical equipment. Part 3. Particular requirement for the essential perfomance of recording and analysing electrocardiographs, IEC, Geneva (1996), 75p.

Authors' Information

Nataliya Bilous – Ph.D., head of ITLCVS laboratory, professor of Kharkov National University of Radio Electronics, Kharkov, Ukraine; e-mail: belous@kture.kharkov.ua

Michael Bondarenko – professor of software department, rector of Kharkov National University of Radio Electronics, president of Ukrainian association of distance learning, academician of the Ukrainian academy of science of higher school: belous@kture.kharkov.ua

Gleb Kobzar – Researcher of ITLCVS laboratory, Kharkov National University of Radio Electronics, Kharkov, Ukraine; e-mail: glebkobzar@yahoo.com

Alexey Krasov – Master of Software Department, Kharkov National University of Radio Electronics, Kharkov, Ukraine; e-mail: belous@kture.kharkov.ua

Artyom Rogozyanov – Master of Software Department, Kharkov National University of Radio Electronics, Kharkov, Ukraine; e-mail: belous@kture.kharkov.ua